Journal of Theoretical and Applied Information Technology
15th October 2022. Vol.100. No 19
© 2022 Little Lion Scientific
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

USING IOT AND ML FOR FOREST FIRE DETECTION, MONITORING, AND PREDICTION: A LITERATURE REVIEW

MOUNIR GRARI[1], MIMOUN YANDOUZI[2], IDRISS IDRISSI[1], MOHAMMED BOUKABOUS[1], OMAR MOUSSAOUI[1], MOSTAFA AZIZI[1], AND MIMOUN MOUSSAOUI[1]

[1]MATSI Lab., ESTO, Mohammed First University, Oujda, Morocco

[2]LARI Lab., FSO, Mohammed First University, Oujda, Morocco

E-mail: m.grari@ump.ac.ma

ABSTRACT

Forests are large areas gathering trees and other plants. They are so important for protecting the environment; they filter air and water, provide food and shelter for animals, and help regulate the climate. Wildfires are one of major hazards of global warming; they destroy forests and speed up the deforestation phenomenon. Other wildfires are also caused by human errors in wilderness environments. Dry vegetation fuels a wildfire's rapid ignition and spread. It is difficult to extinguish flames even with the best efforts of forest firefighters. Smoke and air pollution from wildfires may harm human health and ruin property. Forest fires are difficult to detect at time or to anticipate it, because they spread rapidly. Early-warning systems that they are more accurate are really needed. These systems could be implemented with IoT (Internet of Things), machine learning (ML), or deep learning (DL). In this paper, we focus on this direction of research and we examine literature proposals utilizing IoT and DL to detect wildfires and their spread via a comprehensive evaluation and comparison of existing works.

Keywords: *Forest Fire, Wildfire, IoT, Machine Learning (ML), Deep Learning (DL).*

1. INTRODUCTION

The term 'forest' refers to a large area of land, densely forested with trees and other plants. For many reasons, forest ecosystems are critical. Millions of plants and animals call forests their homes. Additionally, they assist in climate regulation, filter air and water, and provide a variety of valuable resources. Despite their value, forests really face numerous threats, like destruction, wildfires, or deforestation. Numerous forests are eliminated to make room for agriculture or to extract valuable resources such as timber and minerals. Additionally, global warming poses a significant threat to forests. Because of fires, pests, and diseases, forests are increasingly threatened as the Earth's climate changes. It is critical to safeguard forests that are real homes of animals and plants. By adopting environmentally friendly choices, we can all contribute to forest preservation [1].

While forest fires spontaneously occur in a variety of ecosystems, they could be extremely destructive to people, properties, and natural resources. These fires are frequently sparked in wild areas by lightning or human neglect. With conducive environmental conditions, a wildfire can ignite quickly and broadly over large areas, fueled by dry vegetation. Forest firefighters often deploy all their efforts to contain and extinguish wildfires, it takes them days to stop it, and some of them die for this end. Wildfire smoke and air pollution can cause a real health risk, and the flames can destroy or damage homes and businesses. In order to safeguard homes and communities against wildfire dangers, it is critical to have a fire prevention policy and disaster response program [2].

The task of detecting and predicting wildfires is not obvious, as they can ignite anywhere and spread rapidly. However, with the help of technological solutions involving IoT and artificial intelligence, it is possible to develop early-warning systems with relevant accuracy. Using key sensors to measure changes in temperature, humidity, and wind speed, as well as to detect the presence of smoke and fire, is a relevant way to accomplish this task, according to our opinion. The collected data from these measures could be archived, and next used to develop ML models capable of forecasting the likelihood of a fire igniting. We can develop models that predict how a given fire will progress under various conditions by analyzing data from previous fires. Built fire datasets will be a valuable mean to assist firefighters and other emergency responders facing efficiently wildfires. Additionally, it may aid in identifying areas at high risk of wildfires, allowing for the implementation of preventative measures [3].

By conducting a systematic review of the literature, we examine the possibility of using IoT and deep learning to detect and predict wildfires. This paper is structured as follows. The second section covers the terminological aspect of this topic and gives the background of used technologies. The third section discusses the adopted methodology of our literature review. Before concluding, the fourth section makes a synthesis of our findings.

2. BACKGROUND

2.1 Wireless Sensor Networks (WSN)

A WSN is a network of autonomous sensors that can monitor physical or environmental conditions like temperature, and transmit their data to a central location. This latter can be either a standalone centralized unit or a cluster head (a node within the WSN that has the responsibility of collecting and sending sensor data to the centralized unit). Wireless sensor networks are composed of nodes, which are often battery-operated, autonomous, and self-contained with sensors, a radio transceiver, and an onboard signal-processing unit. Data collected by the sensor nodes are processed, then transmitted wirelessly to the centralized unit using multi-hop wireless links [4].

WSNs have many potential applications in a variety of fields, such as military, industrial, commercial, and home applications. The main benefits of WSNs appear in their use of monitoring remotely physical and environmental conditions over a wide area (without the need for physical wires or cables) under reasonable budgets. WSNs are often more flexible and easier to install than wired networks. In addition, WSNs are often more robust and reliable than wired networks due to their distribution and redundancy [5].

2.2 Internet of Things (IoT)

IoT is a term that refers to a future in which everyday objects are connected to the internet and capable of exchanging data. These objects can range from watches to refrigerators. The concept behind the IoT is that by connecting these devices to the internet, they can be remotely controlled and monitored. For instance, people could use their phones to turn on the lights in their homes or adjust the refrigerator's temperatures [6].

The IoT is = rapidly gaining popularity. Numerous companies are developing products that leverage IoT technologies. IoT has a plethora of potential applications. Home automation, health care, and city management are just a few examples of the IoT's most popular applications. For instance, home automation is gaining popularity as people become more interested in remotely controlling their homes [7].

IoT in reality is inspired from a WSN and internet, but with key improvements. IoT is a network of physical devices, vehicles, home appliances, and other objects that are embedded with electronics, software, sensors, and connected to the internet, and can communicate between each other. Compared to WSN, IoT is used not only for monitoring and data collection, but also for control.

2.2.1 IoT protocols.

IoT protocols can be divided into two categories: communication protocols and application protocols.

Communication protocols define how devices connect to and communicate with each other. These protocols can be based on different technologies, such as Wi-Fi, Bluetooth, Zigbee, and LoRa. Each has its own strengths and weaknesses, and the best protocol for a given application will depend on the specific requirements [8].

- ✓ Wi-Fi: is a widely used protocol for internet connectivity, and it can also be used for IoT applications. It has a good range and data throughput and is widely supported by devices and infrastructure. However, it can be power-hungry and is not well suited for applications that require very low data rates or long battery life.
- ✓ Bluetooth: is another popular protocol for IoT, and it has the advantage of being low-power and supporting very low data rates. It is often used for short-range applications where power consumption is a concern, such as in wearables. However, its range is limited, and it may not be suitable for some types of applications.
- ✓ Zigbee: is a low-power protocol that is often used for IoT applications that require long battery life. It has a good range and supports mesh networking, which can be useful for certain types of applications. However, it has relatively low data throughput and may not be suitable for applications that require high data rates.
- ✓ LoRa: is a long-range, low-power protocol that is gaining popularity for IoT applications. It has

an excellent range and can support very low data rates, making it ideal for applications that require long battery life. However, it is not as widely supported as some other protocols, and may not be suitable for all applications.

While the Zigbee and Bluetooth protocols are useful for connecting devices wirelessly, they are not well suited for applications that require long-range or low power consumption. The LoRa protocol is designed specifically for low-power and long-range applications. LoRa allows devices to communicate over distances of up to 15km, making it ideal for IoT applications that require long-range connectivity [9].

Application protocols define how data is exchanged between devices and how applications can access and use that data. Many different application protocols can be used for IoT devices, depending on the specific needs of the devices and the network [10]. Some common protocols that are used for IoT applications include MQTT, CoAP, HTTP, XMPP, and AMQP [11]:

- ✓ MQTT: a popular protocol for handling data from IoT devices, as it is lightweight and can be used over unreliable networks.
- ✓ CoAP: a protocol designed specifically for resource-constrained IoT devices, as it is very lightweight and efficient.
- ✓ HTTP: a common protocol that is used for many different types of networking applications, including IoT.
- ✓ XMPP: a protocol that is commonly used for instant messaging applications, but can also be used for IoT applications.
- ✓ AMQP: a protocol that is designed for reliable message queuing, and is often used in IoT applications that require high reliability.

2.2.2 IoT cloud platforms

IoT cloud platforms provide a comprehensive and centralized way to manage the data and connectivity of IoT devices. These platforms enable enterprises to remotely monitor and manage IoT devices and connect them to various applications and data sources. IoT cloud platforms also offer features such as device management, security, data management, and analytics [12].

There are many different types of IoT cloud platforms available, each with its own unique benefits and features. Some of the most popular IoT cloud platforms include [13], [14]:

- ✓ AWS IoT: Amazon's cloud platform offers a comprehensive set of features for managing and deploying IoT applications.
- ✓ Google Cloud IoT: Google's platform provides powerful data processing and analysis capabilities, making it ideal for complex IoT applications.
- ✓ IBM Watson IoT: IBM's platform offers a robust set of features for building cognitive IoT applications.
- ✓ Microsoft Azure IoT: Microsoft's cloud platform provides a comprehensive set of services and tools for deploying IoT applications.
- ✓ Thingsboard: is an open-source IoT platform that allows to connect devices and applications to the cloud and to other devices. It provides access to data and commands from the devices and allows to send commands to the devices.
- ✓ ThingSpeak: is an IoT analytics platform that allows to collect, visualize, and analyze data from devices. It also allows to send commands to devices.
- ✓ BOLT Cloud: A highly integrated IoT platform for developers that enables users to rapidly and simply construct IoT projects and products.

These are just some examples of the many different IoT cloud platforms available today. Each platform has its own unique benefits and features, so it is important to choose the one that best suits the specific needs.

2.3 Machine Learning (ML)

Machines can learn in a variety of ways. Some machines employ artificial intelligence, while others employ machine learning, a subfield of artificial intelligence concerned with the design and development of algorithms capable of learning from and forecasting data. Machine learning algorithms can be used to discover patterns in data and make future predictions [15].

Machine learning is a technique for teaching computers to learn from data without explicitly programming them to do so. It entails exposing computers to large data sets and then allowing them to discover patterns and relationships in the data on their own. This can be accomplished through the use of a variety of techniques, such as artificial neural networks, decision trees, and genetic algorithms [16]. Machine learning algorithms can be used for many different tasks, including [17]:

- ✓ Regression: Used to predict a continuous value, such as a price, a probability, or fire in our case study. Common regression algorithms include linear regression, logistic regression, and support vector regression.
- ✓ Classification: Used to predict a discrete value, such as a class label (e.g., "Fire" or "No Fire"). Common classification algorithms include

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

ANN, decision trees, k-nearest neighbors, and support vector machines.

- ✓ Clustering: Used to find groups of similar examples. Common clustering algorithms include hierarchical clustering and k-means clustering.
- ✓ Dimensionality reduction: Used to reduce the number of features in a data set. Common dimensionality reduction algorithms include principal component analysis and kernel principal component analysis.

Machine learning is a rapidly expanding field that is being applied in a variety of industries, including finance, healthcare, manufacturing, and transportation. Additionally, it is used in a variety of research fields, including natural language processing and computer vision.

Artificial Neural Network (ANN)

ANN is a computational model inspired by the structure and functionality of the biological neural networks. Structurally, an ANN is composed of a set of interconnected processing nodes, or neurons, where each neuron is a mathematical function that computes a weighted linear combination of its input values. Functionally, an ANN performs a mapping of input values to output values [18].

The interconnections between neurons are called synaptic weights, and these weights can be adjusted, or learned, to produce the desired mapping. ANNs are capable of learning to approximate any mapping function, given enough data and computational resources. There are different types of neural networks, including feed-forward networks, recurrent networks, and convolutional networks [18].

2.4 Deep Learning (DL)

Deep learning is a subset of machine learning that enables computers to discover patterns and insights in data. It is a highly effective technique for developing sophisticated models capable of learning to recognize objects, textures, and patterns in data. Deep learning is particularly well-suited for tasks that humans find difficult, such as object recognition in images and videos or natural language comprehension. It has been demonstrated to be effective across a broad spectrum of applications, including computer vision, speech recognition, and natural language processing [19].

One of the primary benefits of deep learning is that it enables the training of powerful models using massive amounts of data. These models can then be used to perform complex tasks such as natural language comprehension or object recognition in images. One of the primary drawbacks of deep learning is how difficult it can be to learn how to use it effectively. However, with the appropriate tools and resources, it is possible to develop models that outperform humans across a broad range of tasks [20].

Machine learning is limited in several ways when compared to deep learning. Machine learning algorithms are less adept at dealing with data noise, which means they are more susceptible to being duped by inaccurate or incomplete data. Besides, machine learning algorithms are less effective at generalizing from training data to new data sets, which means they are less effective at making predictions in situations where the data has never been seen before [21].

There are various deep learning algorithms; among the most popular are Convolutional Neural Networks (CNNs) [22], Recurrent Neural Networks (RNNs) [23], and Generative Adversarial Networks (GANs) [24].

2.4.1 Convolutional Neural Networks (CNN)

CNNs, or Convolutional Neural Networks, are a type of neural network that is optimized for image processing. They are similar to other types of neural networks, but they have several features that make them particularly effective at image processing [25]. CNNs are made up of multiple layers (see Figure 1), each of which is dedicated to a specific task. The first layer is the input layer, which is responsible for receiving the image data. The following layer is the convolutional layer, which concatenates the input data. Following this layer is the pooling layer, which pools the input data. The following layer is the fully connected layer, which is responsible for activating the input data. Finally, the output layer is responsible for generating the final output [26].

CNNs are more effective at processing image data than other types of neural networks because they are purpose-built for this purpose. The convolutional layer extracts feature from the input data, while the pooling layer combines these features into a smaller set of parameters. This increases the network's efficiency and capacity for learning. Additionally, the fully connected layer is capable of learning the relationships between these features, which enables the network to produce meaningful outputs [27].

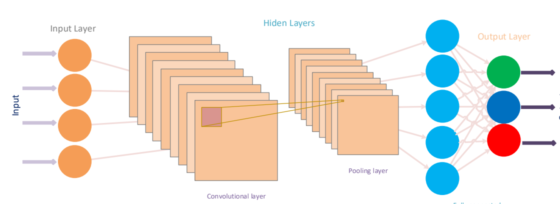

Figure 1: CNN layers architecture

Journal of Theoretical and Applied Information Technology
15th October 2022. Vol.100. No 19
© 2022 Little Lion Scientific

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

2.4.2 Recurrent Neural Network (RNN)

RNNs are a type of neural network in which node connections form a directed graph along a temporal or sequential path. In other words, the output of each node in the sequence is fed as input to the next node in the sequence (see Figure 2). This creates an internal state for the network, allowing it to model temporal dependencies in data – such as natural language understood by humans. RNNs were first developed in the 1980s but have only recently been widely used with the advent of powerful computers and effective training algorithms [27].

RNNs are particularly well suited to tasks that involve sequences of data, such as time series or text data. This is because they can remember information about what has come before in the sequence, which is important for understanding the context of the current data. For example, an RNN could be used to predict the next word in a sentence, based on the words that have come before [28].

There are several different applications for RNNs. One common use case is time series prediction, where an RNN is used to predict the next value in a sequence, based on the previous values. RNNs were also applied in machine translation, speech recognition, and image captioning applications.

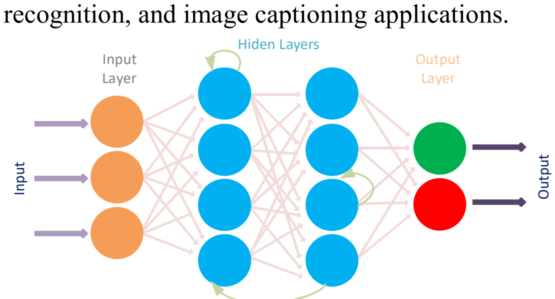

Figure 2: Recurrent Neural Networks layers

While RNNs have several advantages, they also have some limitations. One major limitation is that RNNs struggle to learn patterns that span long periods of time. This is because the information that is passed from one node to the next is forgotten over time. LSTM networks are designed to overcome this limitation, as they contain special nodes that can remember information for long periods of time (see Figure 3).

There are three main types of RNN: long short-term memory (LSTM), gated recurrent unit (GRU), and plain RNN. Each has its own pros and cons, and the type that is best for a given situation depends on the nature of the data and the task at hand [29].

- ✓ LSTMs are the most powerful and flexible type of RNN. They are well-suited for tasks that require long-term memory, such as language translation and text generation. LSTMs are also relatively robust against the vanishing gradient problem, which is a common issue with vanilla RNNs.
- ✓ GRUs are a simplified version of LSTM cells and are well-suited for tasks that do not require the full power of an LSTM. GRUs are faster to train and consume less memory than LSTMs, making them a good choice for applications where resources are limited.
- ✓ Plain RNNs are the simplest type of RNN. They are suitable for tasks that do not require long-term memory and are not as computationally demanding as LSTMs or GRUs. However, plain RNNs are more susceptible to the vanishing gradient problem.

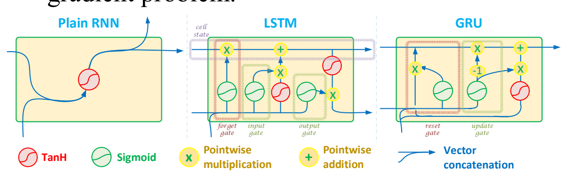

Figure 3: Plain RNN, LSTM, and GRU blocks

2.5 Datasets

A dataset is a structured set of data. It usually contains a set of variables, each with a set of values. A dataset may also contain other sets of data, such as subsets, hierarchies, or networks, they are often used to represent real-world objects, systems, or events [30].

Datasets can be used to store data in a wide variety of formats, including text, images, audio, and video. They can also be used to store data in a more specific format, such as a spreadsheet or database. Datasets can be created manually or generated automatically, they can be created by individuals or organizations, can be small or large, simple or complex, and can be static or dynamic. Datasets are often used in data analysis and data mining. They can also be used for classification, prediction, and optimization.

Datasets about forest fires are important for understanding the extent of the problem and for designing effective mitigation strategies. These datasets can help answer questions about the location, size, and severity of forest fires, as well as the factors that contribute to them. Forest fire datasets are available in a variety of formats, including tabular (which includes data such as sensor data collected) and image/video (contains images or videos of forest fires).

2.6 Evaluation Metrics

In machine learning, evaluation metrics are used to evaluate the performance of the machine learning models, and the appropriate metric to use depends on the specific type of model and the data. Some common evaluation metrics for classification models include accuracy, precision, recall, and f1-score. For regression models, common evaluation metrics include mean absolute error, mean squared error, root mean squared error and R-squared. There is no single perfect evaluation metric. It is always best to use multiple evaluation metrics when assessing a machine learning model.

2.6.1 Accuracy

The accuracy metric is a mathematical formula used to determine the accuracy of predictions made by a machine learning model. The accuracy metric is used to compare the predicted values with the actual values. The accuracy metric is used to assess the performance of a machine and deep learning model. The accuracy metric is a value between 0 and 1, where 1 is the perfect score. The accuracy metric is used to compare the prediction of a machine learning model to the actual values. The accuracy metric is used to assess the performance of a machine learning model [21]. The accuracy is calculated using the formula (1) [31] presented below:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+F} \quad (1)$$

In the case of forest fires, accuracy would tell us how many fires were correctly detected out of the total number of fires. If accuracy is high, then we can be confident that the fire detection system is working well.

2.6.2 Precision, Recall, and F1-score.

In the field of data mining, machine, and deep learning, there are three important metrics used to evaluate the performance of a classifier: precision, recall, and F1-score.

Precision is the proportion of correct positive predictions out of all positive predictions. The recall is the proportion of correct positive predictions out of all actual positive events. The F1-score is the harmonic mean of precision and recall and is a measure of a classifier's accuracy [32]. These metrics are calculated using the formulas (2,3, and 4) [21] presented below:

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1 = \frac{2}{P^{-1}+R^{-1}} \quad (4)$$

Where:

- ✓ TP = True Positive
- ✓ FP = False Positive
- ✓ FN = False Negative

A classifier that is very precise but not very recall-oriented will have a high precision but low recall. A classifier that is very recall-oriented but not very precise will have a high recall but low precision. The ideal classifier would have a high precision and high recall, but this is often not possible.

The trade-off between precision and recall is important to consider when designing a classifier. In some applications, it is more important to have a high precision (even at the expense of recall), while in others, it is more important to have a high recall (even at the expense of precision).

The F1-score is a good metric to use when comparing the performance of different classifiers, as it takes into account both precision and recall.

2.6.3 MAE, MSE, RMSE, and R2

The Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Square Error (RMSE), and the coefficient of determination (R2, or R-squared) evaluation metrics are used to assess the performance of predictive models. Each metric measures the difference between the predicted values and the actual values [32].

MAE is the simplest of the three metrics to calculate. Simply take the average of the absolute value of the difference between the predicted values and the actual values. MAE is easy to interpret, as it gives the average error in the predictions. It can be calculated using the formula (5):

$$MAE = \frac{1}{n}\sum_{j=1}^{n}\left|y_j - \hat{y}_j\right| \quad (5)$$

Where:

- ✓ $n = number\ of\ data\ points$
- ✓ $y_j = observed\ values$
- ✓ $\tilde{y}_j = predicted\ values$

MSE is the mean of the squared difference between the predicted values and the actual values. MSE is more difficult to interpret than MAE, but it is a more accurate measure of differences. It can be calculated using the formula (6):

$$MSE = \frac{1}{n}\sum_{j=1}^{n}\left(y_j - \tilde{y}_j\right)^2 \quad (6)$$

RMSE is the square root of the MSE. RMSE is more difficult to interpret than MAE or MSE, but it is the most accurate measure of differences. It can be calculated using the formula (7):

$$RMSE = \sqrt[2]{\frac{1}{n}\sum_{j=1}^{n}\left(y_j - \hat{y}_j\right)^2} \quad (7)$$

R2 is a measure of the proportion of the variability in the target that is explained by the model. It can be calculated using the formula (8):

$$R2 = 1 - \frac{SE}{SEt} \quad (8)$$

Where:

- ✓ SE = *the sum of squares of the residual errors*
- ✓ SEt = *the total sum of the errors*

Journal of Theoretical and Applied Information Technology
15th October 2022. Vol.100. No 19
© 2022 Little Lion Scientific
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Each of these metrics has its own strengths and weaknesses, and there is no one metric that is best for all situations. MAE is relatively easy to interpret and is often used when there is a need for a quick and dirty assessment of a model's performance. MSE is more commonly used when there is a need for a more detailed analysis. RMSE is often used when there is a need to compare the performance of two or more models. R2 is a good metric to use when there is a need to understand how well the predicted values fit the actual values.

3. FOREST FIRE DETECTION, MONITORING, AND PREDICTION TECHNIQUES

Forest fires are detected, monitored, or predicted using a variety of approaches, which can be divided into two main categories: imagery-based and sensors-based. The first approach by which forest fires are detected is through imaging, this can be accomplished with fixed cameras, satellites, or drones and it allows authorities to get a bird's eye view of the fire, pinpoint its exact location, and get its contour. The second approach that is our review focus, involves the use of sensors that can detect environmental data such as heat, humidity, gases, and so on. These sensors, which can be placed strategically throughout the forest, will send an alert to authorities if they detect a fire [1] (see Figure 4).

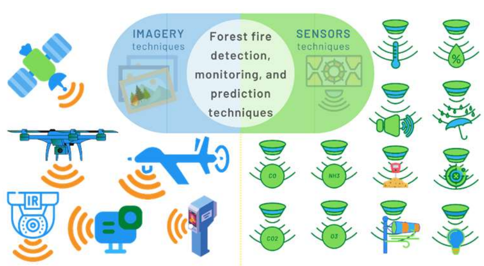

Figure 4: Forest fire detection, monitoring, and prediction; the two main categories

3.1 Imagery-based Detection Techniques

One way to detect forest fires is to use imagery. Imagery can come from many different sources, including satellites, airplanes, and drones. Each of these sources has its own advantages and disadvantages [2].

Satellites are probably the most commonly used source of imagery for forest fire detection. They have the advantage of being able to cover large areas very quickly. However, they can sometimes have trouble picking up small fires, and they can be affected by clouds. One of the main advantages of using satellites for forest fire detection is that they can cover large areas quickly. This is important because forest fires can spread rapidly, making it difficult for ground-based systems to keep track of them [1]. Another advantage of using satellites is that they can provide information about the fire at night when it is often not possible to see the fire from the ground. This is important because many Forest fires start at night and can spread very quickly before they are noticed [33].

There are several different types of satellites that can be used for Forest fire detection, including passive sensors that detect the heat given off by a fire, and active sensors that use a laser or other electromagnetic energy to "see" through the smoke. Some satellites are specifically designed for fire detection, while others, such as weather satellites, can also provide valuable information about a fire. The information provided by satellites can be used by firefighters to plan their attack on a fire, and by fire, managers to monitor the progress of a fire and the spread of smoke. Satellites are an important tool for Forest fire detection, and their use is likely to increase in the future as they become more sophisticated and more widely available [34].

Airplanes and drones are also used for Forest fire detection. They have the advantage of being able to get a closer look at a fire, which can help to identify it more quickly. However, they can be more expensive to use, and they can only cover a small area at a time. One way to do this is by using. By analyzing collected images and videos, it is possible to identify potential fire hotspots and track the progress of the fire. This information can then be used to warn people in the area and help firefighters to better target their efforts [35].

There are a number of different ways to detect forest fires using images and videos. One popular method is to use of heat detection. This involves looking for areas of high temperature in the image or video. This can be done using infrared cameras or other thermal imaging methods.

Thermal imagery is a type of infrared photography that can detect heat sources from a distance. This makes it ideal for detecting forest fires, which are often started by careless campers or hikers who don't realize the risks. In general, the working principle of this method is very simple: the thermal cameras will scan the area and identify the areas with high temperatures. These areas are likely to be the sources of forest fires [36].

Compared with other methods, the use of thermal imagery has many advantages. First of all, it is very

© 2022 Little Lion Scientific
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

quick and effective. By using this method, the firefighters can quickly identify the contours of the area of the fire and focus their efforts on this area. Moreover, this method can also help to detect the potential fires which have not been yet broken out. This is because the high temperatures usually indicate the areas where the fires are about to start. Another advantage of using thermal imagery is that it can be used in all weather conditions. This is because the thermal cameras can still detect high temperatures even in the heavy fog or the dark night. This is very important because the other methods, such as the use of ordinary cameras, will not be effective in these conditions [37], [38].

Infrared gas detectors are a vital tool in the fight against forest fires. By monitoring the presence of infrared radiation in the atmosphere, these detectors can provide an early warning of fires, allowing firefighters to take action to prevent them from spreading [39]. One of the main benefits of using infrared gas detection for fire detection is that it can be done from a distance. This means that firefighters can be alerted to a fire before it has had a chance to spread. This can be crucial in preventing a disastrous wildfire. Another benefit of using infrared gas detection is that it can help firefighters to identify the source of a fire. This can be very helpful in fighting a fire, as it can allow firefighters to target their efforts more effectively [40].

Another popular method is to look for changes in the color of the smoke. This can be done by analyzing the color of the smoke over time or by looking at the smoke plume from different angles. yet another method is to look for changes in the brightness of the image. This can be caused by the fire itself or by the smoke reflecting sunlight. By looking at the brightness over time, it is possible to track the progress of the fire.

Using these camera devices (such as a drone, satellite images, …), it is possible to perform this prediction locally (in the Edge layer) or to send the data to the gateway, where a more capable device (in the Fog layer) may do so. Once the fire service receives the warning, they are able to make the necessary preparations for the forecast blazes on either the Edge or the Fog layer. If a wildfire is predicted, a notification will be issued to the local fire department (see Figure 5).

All of these methods have their advantages and disadvantages. However, by using them together, it is possible to get a more accurate picture of where a fire is and how it is progressing. This information can then be used to help firefighters to better target their efforts and to warn people in the area.

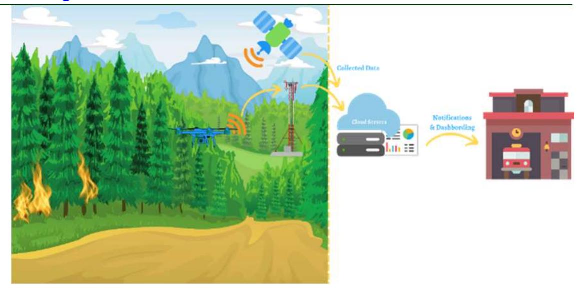

Figure 5: Forest fire monitoring and detection using imagery

3.2 Sensors-based Detection Techniques

A sensor is a device that detects and transforms physical quantities into a signal that can be read by an observer or equipment. There are many different types of sensors, and they are used in a wide variety of applications. Some of the most common applications for sensors are in the detection of forest fires [41].

Sensors are one of the most important tools that we use in order to detect forest fires. By monitoring various environmental factors. One of the best ways to detect a forest fire early is to use sensors. Temperature, humidity, CO, CO2, smoke, light, sound, wind speed, soil moisture, GPS, and pressure sensors can all be used to detect a forest fire.

- ✓ Temperature sensors are the most commonly used type of sensor for Forest fire detection. They can be used to detect hot spots, which are areas where the temperature is significantly higher than the surrounding area. Hot spots can be caused by burning embers or fires.
- ✓ Humidity sensors can also be used to detect forest fires. When the air is very dry, it can help to spread a fire. By measuring the humidity, firefighters can get an idea of how dry the conditions are and whether or not a fire is likely to spread.
- ✓ CO and CO2 sensors can be used to detect the presence of smoke. Smoke is a major indicator of a fire. These sensors can help to give firefighters an early warning that a fire is present.
- ✓ Light sensors can also be used to detect fires. When there is a lot of smoke, the light levels will be lower than normal. This can be used to help identify areas where a fire is burning.
- ✓ Sound sensors can be used to detect the sound of a fire. This can be helpful in determining the location of a fire.
- ✓ Wind speed sensors can be used to determine the rate at which a fire is spreading. The faster the wind is blowing, the faster a fire will spread.

- ✓ Soil moisture sensors can be used to detect the moisture content of the soil. This information can be used to determine the likelihood of a fire spreading.
- ✓ GPS sensors can be used to track the location of a fire. This information can be used to help firefighters to determine the best way to get to the fire.
- ✓ Pressure sensors can be used to measure the amount of pressure in the air. This information can be used to determine the intensity of a fire.
- ✓ O3 sensors can be used to detect the presence of ozone. Ozone is produced when oxygen is burned. This can be used to help identify areas where a fire is present.
- ✓ NH3 sensors can be used to detect the presence of ammonia. Ammonia is produced when vegetation is burned. This can be used to help identify areas where a fire is present.

These are the most used sensors that can be employed to detect forest fires. Tree-mounted sensors that are protected from animals and people while collecting the most data possible from a wide area are ideal for this purpose (temperature, humidity, CO concentration, and other relative measurements). In order to receive and communicate information to and from these sensors' devices without interference, data collected by these sensors is sent to a gateway, which is supposed to be situated in a high position. Gateways take data and send it to the cloud, where it may be used for further analysis, storage, and dashboarding (see Figure 6). By using these sensors, firefighters can get an early warning that a fire is present and take action to prevent it from spreading.

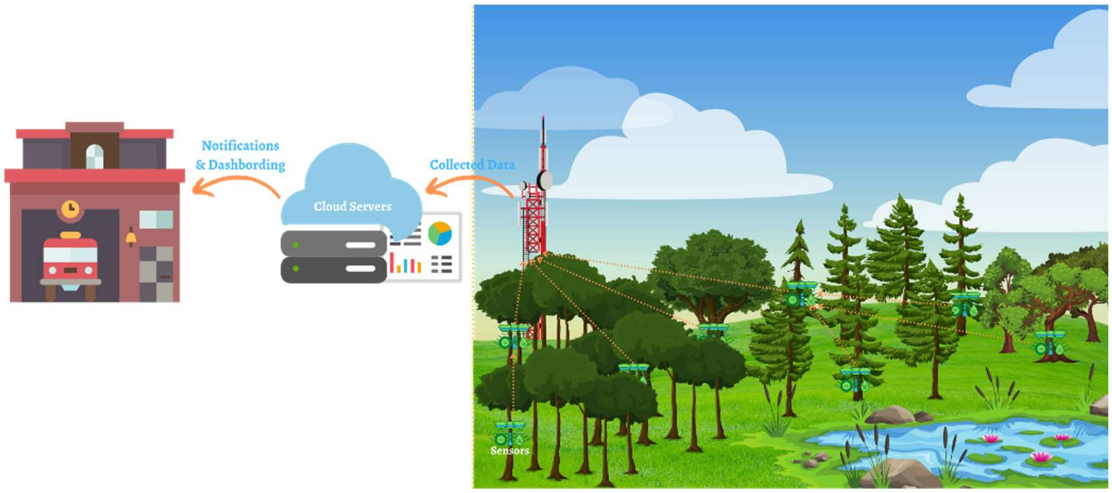

Figure 6: Forest fire monitoring and detection using deployed sensors

4. METHODOLOGY

The search strategy used to retrieve papers on forest fire detection using deep learning and IoT includes searching for papers in the Scopus database; which is the leading abstract and citation database of peer-reviewed research literature, making it the most popular academic search engines and databases, which contains IEEE, Springer, and Elsevier publications. More than 1.8 billion cited references dating back to 1970, and more than 84 million records are indexed in Scopus, making it one of the largest academic search engines in the world [42].

The search terms used were ("forest fire" OR "wildfire") AND ("Machine Learning" OR "ML" OR "DL" OR "Deep Learning") AND (IoT OR "Internet of Things" OR "Wireless Sensor Network" OR "WSN"). Our inclusion criteria for selected papers consider only those that had been published in peer-reviewed journals, and deal with forest fire detection using deep learning and IoT. 41 papers were retrieved using the search strategy described above (see Figure 7). In addition, some of these papers were excluded because they did not meet the inclusion criteria or were just first pages of conference proceedings. The remaining 20 papers were included in the review (see Table 1).

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

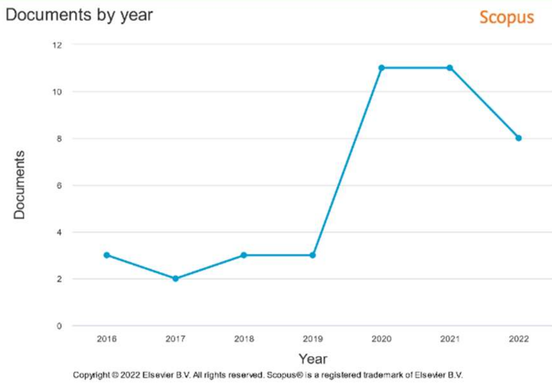

Figure 7: Number of publications per year

5. FINDINGS

The following section analyzes the results of Table 1, 2, and 3. To begin, we will define the comparison criteria used in Table 1:

- ✓ Year: the year in which the paper was published;
- ✓ Objective:
  - o CLA: Classification
  - o REG: Regression
  - o OD: Object Detection
  - o Other objectives
- ✓ ML or DL Model: the used machine or deep learning models.
  - o ANN: Artificial Neural Network
  - o CNN: Convolutional Neural Network
  - o RNN: Recurrent Neural Network
  - o COELMAE: Compressed Sensing and Online Extreme Learning Machine Autoencoder
  - o LSTM: Long Short-Term Memory
  - o HNN: Hebbian Neural Network
  - o AutoML: Automated Machine Learning
  - o MLR: Multiple Linear Regression
  - o GRNN: General regression neural network
  - o LogR: Logistical Regression
  - o LVQ: Learning Vector Quantization
- ✓ EXP/SIM:
  - o EXP: Experience

Journal of Theoretical and Applied Information Technology
15th October 2022. Vol.100. No 19
© 2022 Little Lion Scientific

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Year	Paper	Title	Objective	EXP / SIM	ML OR DL Model	Results	Dataset	Features
2020	[49]	A smart approach for fire prediction under uncertain conditions using machine learning	CLA	SIM	ML	ACC=72%	UCI repository Forest Fires Data Set [63] +Images	X, Y, month, day, FFMC, DMC, DC, ISI, temp (Temperature), RH (Humidity), wind, rain, area
2021	[52]	Sustainable Peatland Management with IoT and Data Analytics	REG	EXP	ML: Multi Variate REG	-	Captured	Atmospheric Data (wind speed, ambient Temperature, relative Humidity, accumulated precipitation), Ground Data (soil Temperature and GWL)
2021	[53]	A comparative analysis of LSTM and ARIMA for enhanced real-time air pollutant levels forecasting using sensor fusion with ground station data	REG	EXP	LSTM	-	Captured	IoT Data: O3, NH3, CO Ground station Data: O3, NH3, CO
2021	[62]	Forest 4.0: Digitalization of forest using the Internet of Things (IoT)	Re view	-	ML, DL	-	-	-
2021	[59]	Effective deployment of sensors in a wireless sensor networks using hebbian machine learning technique	Deploy ment WSN	SIM	HNN	-	-	-
2022	[60]	Towards mountain fire safety using fire spread predictive analytics and mountain fire containment in iot environment	Fire Spread and Burned area predict ion	SIM (QGI S)	ML: AutoML	Burned area: RMSE=2.52 MAD=6.42 Spread: RMSE=1653 MAD=1229	Hallasan's [64], Kaggle Wildfire [65], and UCI repository Forest Fires Data Set [63]	Temperature, wind, Humidity, fire intensity X, Y, month, day, FFMC, DMC, DC, ISI, temp (Temperature), RH (Humidity), wind, rain, area
2022	[54]	A Machine Learning Approach to Weather Prediction in Wireless Sensor Networks	REG	SIM	ML: MLR	MAE=11 RMSE=17.5	Intel Lab dataset [66]	Temperature, Humidity, light, and voltage
2022	[61]	Accurate Location Estimation of Smart Dusts Using Machine Learning	Locali zation	SIM	GRNN	-	-	-
2022	[50]	Forest fire detection system using wireless sensor networks and machine learning	CLA	EXP	ML: REG	ACC=86.36%	Captured (7000r)	Temperature, Humidity, light intensity level, and CO level
		Learning Machine Autoencoder				F1s=92.92%		

- SIM: Simulation

✓ Results: The proposed model's best results, based on the metrics used;
- ACC: Accuracy
- R-square
- MAE
- RMSE
- RECALL
- F1-Score

✓ Dataset: the data used to train and evaluate the proposed Machine Learning model;

✓ Features: Temperature and Humidity, Soil moisture, Pressure…

At first sight, scientific research aimed at forest fire detection using ML, and IoT or WSN techniques, is increasing. More than 80% of the papers on the Scopus database that address this problem, are published over the last three years.

The majority of the papers studied deal with the problem of forest fire detection by classification [43]–[50]. While the papers [51]–[54] worked on Regression to predict fire level, [51] determined the fire risk concerning the hydration level of a peat bog, [52] predicted humidity, and [54] estimated the post-fire air pollution level (forecasting three different air pollution levels such as CO, NH3, and O3) [53]. [55] implemented an object detection technique in combination with Fire Sensor. In [56]–[61] the

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

authors examined complementary aspects of forest fire detection, including the deployment of WSNs, sensor location, and sensor data transmission errors.

Half of the examined papers (up to ~ 10) [43]–[48], [50], [52], [53], [55] were based on real-world experiments, others involved simulation, as for [49], [51], [54], [56]–[61]. It is difficult to compare the results obtained from the works reviewed since they were acquired using several different metrics and datasets, although practically they are very inspiring.

By examining the models utilized, we can clearly categorize these works into two broad categories: ML and DL. The following papers [48]–[52], [54], [56], [60] worked with regression techniques (Logistical, Multi Linear...). On the other hand, the majority of papers on DL [43]–[47], [53], [55], [57]–[59], [61] worked with classification techniques, with the exception of [55] which used image-based object detection. The Dataset is crucial for any scientific research using machine learning and IoT to detect forest fires. Papers [57], [59], [61], [62] made no reference to their used dataset. Meanwhile, the following papers [43]–[48], [50], [52], [53], [55], [56] collected their own datasets without making them publicly available. On the other side, papers [49], [51], [54], [58], [60] used public datasets from the UCI repository (for Forest Fire), the Harvard Shuttle, CortezMorais/Corsican Fire, Hallasan's/Kaggle Wildfire/UCI, and Intel Lab, respectively.

Table 2 clearly shows that the most commonly used characteristics for detecting forest fires are Temperature, Humidity, CO, and Light. However, the papers that used particular characteristics were trying to explore some specific areas. For the use of Sound [44], it seems to be interesting, and we will consider it in our future works.

Table 2: Summary of reviewed literature based on the used characteristics

Paper	Temperature	Humidity	CO	Light	Wind	CO2	Images	Pressure	GPS	GWL	NH3	O3	smoke	Sound	PM	Fire detector	Soil moisture
%	86%	79%	36%	29%	21%	14%	14%	14%	14%	7%	7%	7%	7%	7%	7%	7%	7%
[43]	X	X	X			X			X				X				
[56]	X	X															
[44]	X			X										X			
[45]							X										
[46]	X	X	X			X		X							X		
[55]	X	X		X												X	
[47]	X	X						X	X								X
[48]	X	X			X												
[49]	X	X	X				X										
[52]	X	X			X					X							
[53]			X								X	X					
[60]	X	X			X												
[54]	X	X		X													
[50]	X	X	X	X													

The choice of the communication module is closely related to the targeted switching channel. Apart from the articles that used a complete solution based on a weather station [48], [52], the most commonly used boards are Arduino ones [47], [53] and their generic NodeMCU [55], and the most used communication channel is Wi-Fi, with the exception of [50]; This latter added the SIM800 Module to be able to use the GSM network. [43], [44] implemented the CC2430 and IRIS XM2110 boards, both of which integrate ZigBee technology; the latter boards of which has been discontinued. [45] used a Raspberry pi board to capture images. [47] used a low-quality LoRa32u4 card from BSFrance that is no longer commercially available. [48], [52] collected

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

their own datasets using a weather station, the first on IBM Cloud and the second on MIMOS Malaysia. [43], [44], [50] performed storage on a single remote PC using WSN architecture, the first two using ZigBee and the last using GSM and Radio Frequency. [45] store d the captured images in Microsoft Azure in an IoT architecture with Wi-Fi as a communication channel. [46] used ThingsBoard as a Cloud solution in conjunction with WSN architecture and LoRA as communication technology. And [47], [53], [55] have built a Wi-Fi-based IoT architecture with various cloud choices, including Thingspeak, BOLT Cloud, and Micro soft Azure.

addition, the datasets used to this end are mostly synthetic.

The majority of the studied papers use machine learning approaches to address the problem of wildfire detection; just few ones are considering deep learning models. The classification, regression, and object detection algorithms were by far the most popular. According to the findings of our systematic literature review, we conclude that scientific works having combined IoT and machine/deep learning, achieved best performances and constitute a feasibility proof of the potential and the strength of their approach towards detecting and forecasting wildfires.

Table 3: Summary of reviewed literature based on the used boards, sensors, communication channels, WSN/IoT and cloud storage platforms

Year	Paper	Board/module Connexion	Sensors	Communication	WSN/ IoT	Cloud Storage
2016	[43]	CC2430	EC805-CO NeMOTO, S-100 ELT, MS5100 OGAM, SHT11 SENSIRON, LeadTek GPS 9546	ZigBee	WSN	Remote Server
2018	[44]	IRIS XM2110	Expansion Connector for Light, Temperature and Sound	ZigBee	WSN	Personal Computer
2020	[45]	Raspberry Pi	Camera	WIFI	IoT	Microsoft Azure
2020	[46]	LoRa32u4	BME280, Nova SDS011, MH-Z14A-CO2, ZE07-CO	Lora	WSN	ThingsBoard
2020	[55]	NodeMCU Raspberry PI	DHT11, Fire Sensor, Ambient Light check, LDR Module	WIFI	IoT	Thingspeak
2020	[47]	Arduino UNO+/Bolt	DHT11, YL-69, BMP280 GPS Sensor	WIFI	IoT	BOLT Cloud
2020	[48]	Weather station	-	-	-	IBM Cloud
2021	[52]	Weather station	AGROMIST (Piezometers)	LORA	IoT	MIMOS Malaysia
2021	[53]	Arduino UNO	MQ-7 MQ-131 MQ-135 Optical Dust Sensors	WIFI	IoT	Microsoft Azure
2022	[50]	Arduino nano+nrf24L01 + SIM800	DHT22, LDR, MQ9	GSM/RF	WSN	PC+ Arduino nano+nrf24L01+ SIM800

6. CONCLUSION

In this paper, we conducted a systematic review of the scientific literature that addressed the challenge of detecting and predicting forest fires using IoT and machine/deep learning. The performed data analysis revealed that the features mostly used to identify and detect forest fires are temperature, humidity, CO, and light. We also learned that the communication channels deployed in this context are mostly based on one of these protocols WIFI, ZigBee, or GSM. In

ACKNOWLEDGMENT

This work is supported by the Mohammed First University, under the PARA1 Program (Low-cost, real-time Forest Fire Detection System based on Wireless Sensor Networks - SDF-RCSF).

REFERENCES:

[1] M. Grari, I. Idrissi, M. Boukabous, O. Moussaoui, M. Azizi, and M. Moussaoui, “Early Wildfire Detection using Machine Learning Model

Deployed in the Fog / Edge Layers of IoT," *Indones. J. Electr. Eng. Comput. Sci.*, 2022.

[2] M. Yandouzi *et al.*, "Review on Forest Fires Detection and Prediction using Deep Learning and Drones," *J. Theor. Appl. Inf. Technol.*, 2022.

[3] A. A. A. Alkhatib, "A Review on Forest Fire Detection Techniques:," *http://dx.doi.org/10.1155/2014/597368*, vol. 2014, Mar. 2014, doi: 10.1155/2014/597368.

[4] C. S. Raghavendra, K. M. Sivalingam, and T. Znati, *Wireless sensor networks*. Springer, 2006.

[5] J. A. Stankovic, "Wireless sensor networks," *Computer (Long. Beach. Calif).*, vol. 41, no. 10, pp. 92–95, 2008, doi: 10.1109/MC.2008.441.

[6] I. Idrissi, M. Azizi, and O. Moussaoui, "A Stratified IoT Deep Learning based Intrusion Detection System," in *2022 2nd International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET)*, Mar. 2022, pp. 1–8, doi: 10.1109/IRASET52964.2022.9738045.

[7] I. Idrissi, M. Mostafa Azizi, and O. Moussaoui, "A Lightweight Optimized Deep Learning-based Host-Intrusion Detection System Deployed on the Edge for IoT," *Int. J. Comput. Digit. Syst.*, Jul. 2021.

[8] S. Al-Sarawi, M. Anbar, K. Alieyan, and M. Alzubaidi, "Internet of Things (IoT) communication protocols: Review," *ICIT 2017 - 8th Int. Conf. Inf. Technol. Proc.*, pp. 685–690, Oct. 2017, doi: 10.1109/ICITECH.2017.8079928.

[9] J. Haxhibeqiri, E. De Poorter, I. Moerman, and J. Hoebeke, "A Survey of LoRaWAN for IoT: From Technology to Application," *Sensors 2018, Vol. 18, Page 3995*, vol. 18, no. 11, p. 3995, Nov. 2018, doi: 10.3390/S18113995.

[10] B. H. Çorak, F. Y. Okay, M. Güzel, Ş. Murt, and S. Ozdemir, "Comparative Analysis of IoT Communication Protocols," *2018 Int. Symp. Networks, Comput. Commun. ISNCC 2018*, Nov. 2018, doi: 10.1109/ISNCC.2018.8530963.

[11] D. Soni and A. Makwana, "A SURVEY ON MQTT: A PROTOCOL OF INTERNET OF THINGS(IOT) MP-Index View project Analysis and Survey on String Matching Algorithms for Ontology Matching View project A SURVEY ON MQTT: A PROTOCOL OF INTERNET OF THINGS(IOT)," 2017.

[12] S. Tayeb, S. Latifi, and Y. Kim, "A survey on IoT communication and computation frameworks: An industrial perspective," Mar. 2017, doi: 10.1109/CCWC.2017.7868354.

[13] P. P. Ray, "A survey of IoT cloud platforms," *Futur. Comput. Informatics J.*, vol. 1, no. 1–2, pp. 35–46, Dec. 2016, doi: 10.1016/J.FCIJ.2017.02.001.

[14] A. A. Ismail, H. S. Hamza, and A. M. Kotb, "Performance Evaluation of Open Source IoT Platforms," *2018 IEEE Glob. Conf. Internet Things, GCIoT 2018*, Jan. 2019, doi: 10.1109/GCIOT.2018.8620130.

[15] M. Boukabous and M. Azizi, "Crime prediction using a hybrid sentiment analysis approach based on the bidirectional encoder representations from transformers," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 25, no. 2, Feb. 2022, doi: 10.11591/IJEECS.V25.I2.PP.

[16] M. Boukabous and M. Azizi, "Review of Learning-Based Techniques of Sentiment Analysis for Security Purposes," in *Innovations in Smart Cities Applications Volume 4*, Springer, Cham, 2021, pp. 96–109.

[17] V. Nasteski, "An overview of the supervised machine learning methods," 2017, doi: 10.20544/HORIZONS.B.04.1.17.P05.

[18] I. Idrissi, M. Azizi, and O. Moussaoui, "IoT security with Deep Learning-based Intrusion Detection Systems: A systematic literature review," in *4th International Conference on Intelligent Computing in Data Sciences, ICDS 2020*, Nov. 2020, pp. 1–10, doi: 10.1109/ICDS50568.2020.9268713.

[19] A. Kherraki and R. El Ouazzani, "Deep convolutional neural networks architecture for an efficient emergency vehicle classification in real-time traffic monitoring," *IAES Int. J. Artif. Intell.*, vol. 11, no. 1, pp. 110–120, Mar. 2022.

[20] I. Idrissi, M. Azizi, and O. Moussaoui, "An Unsupervised Generative Adversarial Network Based-Host Intrusion Detection System for IoT Devices," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 25, no. 2, 2022.

[21] I. Idrissi, M. Azizi, and O. Moussaoui, "Accelerating the update of a DL-based IDS for IoT using deep transfer learning," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 23, no. 2, pp. 1059–1067, Aug. 2021, doi: 10.11591/ijeecs.v23.i2.pp1059-1067.

[22] A. Kherraki, M. Maqbool, and R. El Ouazzani, "Traffic Scene Semantic Segmentation by Using Several Deep Convolutional Neural Networks," *2021 3rd IEEE Middle East North Africa Commun. Conf.*, pp. 1–6, Dec. 2021, doi: 10.1109/MENACOMM50742.2021.9678270.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[23] M. Boukabous and M. Azizi, "A comparative study of deep learning based language representation learning models," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 22, no. 2, pp. 424–432, May 2020, doi: 10.11591/ijeecs.v22.i2.pp424-432.

[24] M. Berrahal and M. Azizi, "Improvement of facial attributes' estimation using Transfer Learning," in *2022 2nd International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET)*, Mar. 2022, pp. 1–7, doi: 10.1109/IRASET52964.2022.9737845.

[25] M. Berrahal and M. Azizi, "Review of DL-Based Generation Techniques of Augmented Images using Portraits Specification," in *4th International Conference on Intelligent Computing in Data Sciences, ICDS 2020*, Nov. 2020, pp. 1–8, doi: 10.1109/ICDS50568.2020.9268710.

[26] M. Berrahal and M. Azizi, "Augmented Binary Multi-Labeled CNN for Practical Facial Attribute Classification," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 23, no. 2, pp. 973–979, Aug. 2021.

[27] I. Idrissi, M. Boukabous, M. Azizi, O. Moussaoui, and H. El Fadili, "Toward a deep learning-based intrusion detection system for iot against botnet attacks," *IAES Int. J. Artif. Intell.*, vol. 10, no. 1, pp. 110–120, Mar. 2021, doi: 10.11591/ijai.v10.i1.pp110-120.

[28] M. Boukabous and M. Azizi, "Multimodal Sentiment Analysis using Audio and Text for Crime Detection," in *2022 2nd International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET)*, Mar. 2022, pp. 1–5, doi: 10.1109/IRASET52964.2022.9738175.

[29] Y. Hu, A. Huber, J. Anumula, and S.-C. Liu, "Overcoming the vanishing gradient problem in plain recurrent networks," Jan. 2018, doi: 10.48550/arxiv.1801.06105.

[30] A. Paullada, I. D. Raji, E. M. Bender, E. Denton, and A. Hanna, "Data and its (dis)contents: A survey of dataset development and use in machine learning research," *Patterns*, vol. 2, no. 11, p. 100336, Nov. 2021, doi: 10.1016/J.PATTER.2021.100336.

[31] M. Hossin and Sulaiman, "A REVIEW ON EVALUATION METRICS FOR DATA CLASSIFICATION EVALUATIONS," *IJDKP) Int. J. Data Min. Knowl. Manag. Process*, vol. 5, no. 2, 2020, doi: 10.5121/ijdkp.2015.5201.

[32] Y. Hammoudi, I. Idrissi, M. Boukabous, Y. Zerguit, and H. Bouali, "Review on maintenance of photovoltaic systems based on deep learning and internet of things," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 26, no. 2, May 2022.

[33] S. J. Goetz, G. J. Fiske, and A. G. Bunn, "Using satellite time-series data sets to analyze fire disturbance and forest recovery across Canada," *Remote Sens. Environ.*, vol. 101, no. 3, pp. 352–365, Apr. 2006, doi: 10.1016/J.RSE.2006.01.011.

[34] A. Shamsoshoara, F. Afghah, A. Razi, L. Zheng, P. Z. Fulé, and E. Blasch, "Aerial imagery pile burn detection using deep learning : The FLAME dataset," vol. 193, 2021.

[35] H. Wu, H. Li, A. Shamsoshoara, A. Razi, and F. Afghah, "Transfer Learning for Wildfire Identification in UAV Imagery," no. Dl, pp. 1–6, 2020.

[36] W. Schroeder, P. Oliva, L. Giglio, and I. A. Csiszar, "The New VIIRS 375m active fire detection data product: Algorithm description and initial assessment," *Remote Sens. Environ.*, vol. 143, pp. 85–96, Mar. 2014, doi: 10.1016/j.rse.2013.12.008.

[37] Y. Li, A. Vodacek, R. L. Kremens, A. Ononye, and C. Tang, "A hybrid contextual approach to wildland fire detection using multispectral imagery," *IEEE Trans. Geosci. Remote Sens.*, vol. 43, no. 9, pp. 2115–2125, Sep. 2005, doi: 10.1109/TGRS.2005.853935.

[38] J. A. Pardo, W. G. Aguilar, and T. Toulkeridis, "Wireless communication system for the transmission of thermal images from a UAV," *2017 Chil. Conf. Electr. Electron. Eng. Inf. Commun. Technol. CHILECON 2017 - Proc.*, vol. 2017-Janua, pp. 1–5, Dec. 2017, doi: 10.1109/CHILECON.2017.8229690.

[39] L. Hua and G. Shao, "The progress of operational forest fire monitoring with infrared remote sensing," *J. For. Res. 2016 282*, vol. 28, no. 2, pp. 215–229, Dec. 2016, doi: 10.1007/S11676-016-0361-8.

[40] C. Paton-Walsh *et al.*, "Measurements of trace gas emissions from Australian forest fires and correlations with coincident measurements of aerosol optical depth," *J. Geophys. Res. Atmos.*, vol. 110, no. D24, pp. 1–6, Dec. 2005, doi: 10.1029/2005JD006202.

[41] P. K. Singh and A. Sharma, "An insight to forest fire detection techniques using wireless sensor networks," *4th IEEE Int. Conf. Signal Process. Comput. Control. ISPCC 2017*, vol. 2017-Janua, pp. 647–653, Sep. 2017, doi: 10.1109/ISPCC.2017.8269757.

[42] Scopus, "Your brilliance, connected," 2022. .

[43] N. M. System, "Real-Time Identification of Smoldering and Flaming Combustion Phases in Forest Using a Wireless Sensor," no. Ccd, 2016, doi: 10.3390/s16081228.

[44] P. Pokhrel and H. S. B, *Advancing Early Forest Fire Detection Utilizing Smart Wireless Sensor Networks*. Springer International Publishing, 2018.

[45] Y. S. Patel, S. Banerjee, R. Misra, and S. K. Das, "Low-Latency Energy-Efficient Cyber-Physical Disaster System Using Edge Deep Learning," in *PervasiveHealth: Pervasive Computing Technologies for Healthcare*, 2020, vol. Part F1656, doi: 10.1145/3369740.3372752.

[46] B. Wiame, E. Moussati, M. Omar, and B. Mohammed, "Early forest fire detection system using wireless sensor network and deep learning," *Int. J. Adv. Comput. Sci. Appl.*, vol. 7, no. 2, pp. 469–505, 2021.

[47] V. Zope, T. Dadlani, A. Matai, P. Tembhurnikar, and R. Kalani, "IoT Sensor and Deep Neural Network based Wildfire Prediction System," in *Proceedings of the International Conference on Intelligent Computing and Control Systems, ICICCS 2020*, 2020, pp. 205–208, doi: 10.1109/ICICCS48265.2020.9120949.

[48] B. S. Negara, R. Kurniawan, M. Z. A. Nazri, S. N. H. S. Abdullah, R. W. Saputra, and A. Ismanto, "Riau Forest Fire Prediction using Supervised Machine Learning," in *Journal of Physics: Conference Series*, 2020, vol. 1566, no. 1, doi: 10.1088/1742-6596/1566/1/012002.

[49] R. Sharma, S. Rani, and I. Memon, "A smart approach for fire prediction under uncertain conditions using machine learning," *Multimed. Tools Appl.*, vol. 79, no. 37–38, pp. 28155–28168, 2020, doi: 10.1007/s11042-020-09347-x.

[50] U. Dampage, L. Bandaranayake, R. Wanasinghe, and K. Kottahachchi, "Forest fire detection system using wireless sensor networks and machine learning," *Sci. Rep.*, pp. 1–11, 2022, doi: 10.1038/s41598-021-03882-9.

[51] A. Kansal, Y. Singh, N. Kumar, and V. Mohindru, "Detection of Forest Fires using Machine Learning Technique : A Perspective," pp. 241–245, 2015.

[52] J. T. Liew *et al.*, *Sustainable Peatland Management with IoT and Data Analytics*, vol. 629 IFIPAI. 2021.

[53] G. Mani and R. Volety, "A comparative analysis of LSTM and ARIMA for enhanced real-time air pollutant levels forecasting using sensor fusion with ground station data," *Cogent Eng.*, vol. 8, no. 1, 2021, doi: 10.1080/23311916.2021.1936886.

[54] S. S. Patil and B. M. Vidyavathi, "A Machine Learning Approach to Weather Prediction in Wireless Sensor Networks," *Int. J. Adv. Comput. Sci. Appl.*, vol. 13, no. 1, pp. 254–259, 2022, doi: 10.14569/IJACSA.2022.0130131.

[55] S. Garg, S. Ahuja, and S. Randhawa, *Real time adaptive street lighting system*, vol. 1192 CCIS. 2020.

[56] T. Zhang, "Faulty Sensor Data Detection in Wireless Sensor Networks Using Logistical Regression," 2017, doi: 10.1109/ICDCSW.2017.37.

[57] A. V. Vidyapeetham, S. Sinha, and A. V. Vidyapeetham, "Self - Localization in Large Scale Wireless Sensor Network Using Machine Learning," pp. 1–5, 2020.

[58] Y. Yu, X. Wu, and S. Yuan, "Anomaly Detection for Internet of Things Based on Compressed Sensing and Online Extreme Learning Machine Autoencoder," in *Journal of Physics: Conference Series*, 2020, vol. 1544, no. 1, doi: 10.1088/1742-6596/1544/1/012027.

[59] S. M. Kusuma, K. N. Veena, and N. Aparna, "Effective deployment of sensors in a wireless sensor networks using hebbian machine learning technique," in *Proceedings - IEEE 2021 International Conference on Computing, Communication, and Intelligent Systems, ICCCIS 2021*, 2021, pp. 268–274, doi: 10.1109/ICCCIS51004.2021.9397148.

[60] Imran, N. Iqbal, S. Ahmad, and D. H. Kim, "Towards mountain fire safety using fire spread predictive analytics and mountain fire containment in iot environment," *Sustain.*, vol. 13, no. 5, pp. 1–23, 2021, doi: 10.3390/su13052461.

[61] S. Bashir, O. A. Malik, D. Teck, and C. Lai, "Accurate Location Estimation of Smart Dusts Using Machine Learning," 2022, doi: 10.32604/cmc.2022.024269.

[62] R. Singh, A. Gehlot, S. Vaseem Akram, A. Kumar Thakur, D. Buddhi, and P. Kumar Das, "Forest 4.0: Digitalization of forest using the Internet of Things (IoT)," *J. King Saud Univ. - Comput. Inf. Sci.*, 2021, doi: 10.1016/j.jksuci.2021.02.009.

[63] P. Cortez and A. Morais, "A Data Mining Approach to Predict Forest Fires using Meteorological Data," *Proc. 13th Port. Conf. Artif. Intell.*, pp. 512–523, 2007, [Online].

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Available: http://www.dsi.uminho.pt/~pcortez/fires.pdf.

[64] Imran, S. Ahmad, and D. H. Kim, "A task orchestration approach for efficient mountain fire detection based on microservice and predictive analysis in IoT environment," *J. Intell. Fuzzy Syst.*, vol. 40, no. 3, pp. 5681–5696, Mar. 2021, doi: 10.3233/JIFS-201614.

[65] "Forest Fires Data Set|Kaggle," 2007. https://www.kaggle.com/elikplim/forest-fires-data- (accessed May 27, 2022).

[66] "Intel Lab DataSet." http://db.csail.mit.edu/labdata/labdata.html (accessed May 17, 2022).